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Article

Advanced Identification of Prosodic Boundaries, Speakers and Accents Through Multi-Task Audio Pre-Processing and Speech Language Models

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Abstract: In recent years the advances in deep neural networks (DNNs) and large language models (LLMs) have led to major breakthroughs and new levels of performance in Natural Language Processing (NLP), including speech processing related tasks. Based on these new trends, new models such as Whisper and Wav2Vec 2.0 achieve robust performance in speech processing tasks, even in speech-to-text translation and end-to-end speech translation, far exceeding all previous results. Although these models have shown excellent results in real-time speech processing, they still have some accuracy issues for some tasks and high latency problems when working with large amounts of audio data. In addition, many of them need audio to be segmented and labelled for speech synthesis and annotation tasks. Speaker diarisation, background noise detection, prosodic boundary detection and accent classification are some of the pre-processing tasks required in these cases. In this study we will fine-tune a small Wav2Vec 2.0 base model for multi-task classification and audio segmentation. A corpus of spoken American English will be used for the experiments. We intend to explore this new approach and, more specifically, the performance of the model with regards to prosodic boundaries detection for audio segmentation, and advanced accent identification.

Keywords: speech processing; prosodic boundaries detection; speaker change detection; accent classification; Transformer architecture; Wav2Vec2; NLP; multi-task classification

1. Introduction

Speech is the basic form of communication that humans use every day. Because of this, the possibility to communicate with machines through speech has been an interest for many decades. Over the past few years, language and speech models have acquired significant importance in society, mainly due to the recent advances in Natural Language Processing (NLP) and deep neural networks (DNNs). Current models, like Whisper [1] and Wav2Vec 2.0 [2] allow users to have fluent communication with conversational bots, either over text or speech, in real time. The improvements in speech processing have also been reflected in many other system features, for instance, automatic captioning of speech generation for artificial text readers.

Despite these improvements, there are still many scenarios where speech processing needs improvement. Automatic Speech Recognition (ASR) has achieved high scores in performance for common languages, but for low-resource languages, the performance of ASR models is still far from acceptable. In the case of the Arabic language, the word error rate is around 25% or even higher in some cases [3,4]. As demonstrated in [5],to improve their performance, ASR models can be trained applying pre-processing techniques such as segmentation, word modeling or detection of different environmental or speaker variations. These tasks are modeled as speech classification tasks and can be easy to address when sufficient labelled data is available. However, for many languages, it is hard to find enough transcribed and labelled data to train a robust ASR model [6].

In this work, we propose a pre-processing speech model that can perform three tasks at once: prosodic boundary detection (PBD), speaker change detection (SCD) and accent classification (AC).

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Our hypothesis is two-fold: (i) that a Wav2Vec 2.0 base model, as a feature extractor block, can be fine-tuned to extract the features from the audio that are needed to perform the three classifications tasks correctly, and that (ii) this transformer block can generate context representations that share all these features. Thus, the most distinctive feature of our model is, precisely, that it is trained only on audio data, which can help to improve speech recognition performance in terms of precision and resource optimisation.

The rest of the text is organised as follows. Section 2 presents a brief overview about past and recent methods for speech processing. Section 3 describes the methodology and materials used in our experiments. Section 4 reports the experimental results, which are then discussed in Section 5. Finally, Section 6 provides the main conclusions and directions for future work.

2. A Brief Overview

In computer science, speech processing has been defined as the study of speech signals and their processing methods. It encompasses a range of tasks, including classification, recognition, transformation, and generation of speech data, among others. Speech processing tasks have traditionally been based on signal processing [7,8] and linguistic features [9–11] until the growth of Deep Learning (DL) [12–15] In this section, we focus on DL-based techniques applied to three tasks which are particularly relevant to our research: phrase boundary detection (PBD), speaker change detection (SCD) and accent classification (AC). As a convenient theoretical framework, a short description of the techniques applied to these tasks before and after the popularity of DNNs will be presented in order to locate this study in context.

Before Deep Learning, Hidden Markov Models (HMM) [8,16] were currently applied for speech recognition (ASR) and became the dominant paradigm until DNNs started to outperform them [17,18]. Other speech tasks, such as voice activity detection (VAD), speaker recognition and diarisation, prosodic detection and segmentation, among others, play an important role as speech pre-processing tasks to ensure optimal performance in ASR and speech generation (text-to-speech, TTS). Regarding these tasks, numerous alternative methods have been employed prior to the emergence of DNNs. Signal processing algorithms and linguistic feature methods have demonstrated a notable performance for VAD [7], speaker diarisation [19], classification problems [20], and prosodic-related tasks [10].

Even though some of the former methods and algorithms are still in use [21,22], DNNs are currently the most popular methods for speech pre-processing, as well as for ASR, to the point where most of the new methods for these tasks are based on or derived from DNNs (see [23] for a comprehensive review).

2.1 Speech Processing Methods and Techniques

As DNNs became the standard for ASR tasks, the encoder-decoder architecture obtained the most promising performance. In this approach, the encoder extracts features from the input speech, while the decoder transforms those features into the desired output, namely a transcription [24]. In this manner, the encoder learns to generate representations or embeddings that represent the extracted features. A number of different methods of representation is employed in the literature for speech processing tasks. For instance, i-vectors [25], d-vectors [26] and x-vectors [27] are convolutional NNs (CNN) and recurrent NNs (RNN)-based embeddings that have resulted in improved performance of tasks such as speaker diarisation or VAD. However, Transformer NNs [28] have surpassed RNNs and CNNs in the context of speech processing tasks. The utilisation of self- and cross-attention Transformer NNs allows parallelisation and performance improvements that explain the success of them in Natural Language Processing (NLP) tasks [29].

2.2 Automatic Speech Segmentation

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Despite the mentioned computational progress, automatic speech segmentation is still one of the most difficult challenges in speech processing. The variation in speaker characteristics, speaking style and environment make the learning process of prosodic boundaries hard for machines [30]. However, detecting and processing prosodic phrasing is relevant for many speech processing tasks as it can help to improve naturalness in speech synthesis and to enhance audio data for training [31]. In the case of speech synthesis, the common scenario for the detection of prosodic boundaries is performed by relying solely on text [32], while other systems rely solely on acoustic information [33], or on a combination of both lexical and acoustic information [21]. For the purpose of this study, we have opted for the detection of prosodic boundaries based solely on acoustic information (cf. section 3. Materials and methods).

Speaker change detection (SCD) is another speech segmentation task used to determine the boundaries between speakers in a conversation. In simpler words, SCD is the action to detect the moments when a speaker stops talking and another speaker starts to talk, regardless of the identity of the speakers. SCD is part of speaker diarisation systems (who talks and when) [34] but it is also useful for speaker tracking in video data [35] and for transcribing audio with multiple speakers [36]. There are many approaches to perform this task based on DNNs such as the previously mentioned x-vectors [37] or methods based on self-attention mechanisms [38,39]. Overlapped segments (i.e. several speakers talking at the same time) are a common, recurrent problem in SCD. Many of the existing methods opt for the omission of the overlapped segments. However, similar DNNs-based approaches are being applied specifically to overlapped speech detection [40–42]. Besides, adding extra information during training through multitasking techniques has shown that multitask models can reach better results than models trained for only one task [43].

2.4 Accent Identification

Before DNNs, studies in accent identification focused on leveraging linguistic features in statistical approaches. For instance, some of the features that have been combined with statistical analysis are prosodic parameters, syllable structure and speaker characteristics [20,44,45]. Recent studies are centered on DNNs for spoken language identification [46], the generation of representations around features related to accent identification [47–49] or other DL approaches for accent classification [50–52]. Other recent approaches have explored the possibilities of combining accent identification and ASR as a viable way to improve the performance of ASR models [53]. It is notable to mention that some methods, like the one presented by Ghorbani and Hansen [54], have been able to reach better scores than human-perceived scores.

2.5 Joint and Multitask Learning in Speech Processing

Joint learning and multitask learning are both approaches used in machine learning to leverage shared information across tasks. In speech processing, this approach has demonstrated to be beneficial and to get better performance in many tasks [55]. The method presented in [56] shows that joint training could help the encoder of the NN to learn transferable, robust, and problem-agnostic features that carry on relevant information from the speech signal, which contributes to discovering general representations. For speech segmentation, joint and multitask frameworks have been applied to prosodic boundaries detection and SCD with successful results [33,43,57]. With regards to joint learning methods which involve accent classification, recent studies have shown high accent classification performance by adding this task to speech recognition models [58–61].

3. Material and Methods

The main goal of the research presented in this paper is to develop an innovative multitask training approach for PBD, SCD and accent classification by relying only on acoustic information. To address this multitask problem, we have fine-tuned a Wav2Vec 2.0 model for audio frame classification with three classification layers on top of the model, one layer for each task. For this

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experiment, we have used an American English oral corpus as a base dataset for training and validation of the models. This corpus has been pre-processed using different methods for each task, which has led to the generation of new datasets adapted for the purpose of the experiment. The following sections provide detailed information on the base dataset selected and the transformations applied to generate the final datasets, as well as the methods applied for the training, evaluation and validation of the models.

3.1 Speech Corpus Used in the Experiment

The selected corpus for the experiment is the Santa Barbara Corpus of Spoken American English (SBCSAE)[1] [62]. This is a prosodic annotated speech corpus (also named spoken corpus), which encompasses a total of 60 transcribed and annotated conversations, including the timestamps at the level of individual intonation units. The corpus is based on a large body of recordings of naturally occurring spoken interaction from all over the United States, representing a wide variety of people of different regional origins, ages, occupations, genders, and ethnic and social backgrounds. The predominant form of language use represented is face-to-face conversation, but the corpus also documents many other ways people use language in their everyday lives: telephone conversations, card games, food preparation, on-the-job talk, classroom lectures, sermons, story telling, town hall meetings, tour-guide spiels, and more. The transcriptions are formatted in one utterance per line, together with the initial and final timestamps, the name of the speaker and the intonation information of the utterance. In addition, the metadata of each conversation includes a short description and the location where it was recorded. All this information makes the SBCSAE a useful dataset for many supervised learning tasks in speech processing. Given the purpose of this work, we are specifically interested in the timestamps for SCD and PB, and the location information for the accent detection.

3.2 Data Preparation

This section covers all the automatic pre-processing and annotation tasks applied to the dataset used for the experiments. The two first subsections explain the design of the annotation process for each task, while the last one describes how all the processes have been applied automatically.

3.2.1 Audio Frame Labels

Audio segmentation can be seen as the act of slicing the audio into pieces following a specific criterion. Our approach aims to detect the specific frames where the speaker finishes an utterance or ends their intervention. For this reason, we needed to define the frames and assign specific labels for each frame. We have followed the methodology presented in [63] where they have trained a prosodic boundary detection (PBD) model for the Czech language. In their work, the authors assigned a label every 20ms of audio, giving a 1, if the frame contains a boundary, or a 0 if not. In addition, to avoid delays from the manual annotation, the frames around each prosodic boundary (PB) were given a label between 0 or 1, thus creating a linearly increasing and decreasing interval. For the PBD task, we have followed this exact same method applied to the SBCSAE.

The SBCSAE includes the name of the speaker for each utterance in the transcript file. We used this information to create the reference data for the SCD task in a similar manner to previously mentioned PB references: we have given the label 1 to the frames when a new speaker starts to talk and 0 for the next utterances of the same speaker. This method for label setting has one problem: it does not consider whether two or more speakers are talking at the same time. To address this issue, the SBCSAE corpus includes the labels “BOTH” and “MANY” when more than one person is speaking. This annotation has been adapted to our labelling method by assigning label 2 to the frames that correspond to these utterances. This is also known as Overlapping Speech Detection (OSD). In addition, the corpus also includes specific labels for timestamps where a sound or environmental

[1] The SBCSAE corpus can be accessed and downloaded here: https://www.linguistics.ucsb.edu/research/santa-barbara-corpus

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noise occurs. Following our labelling process, we have assigned label 3 to these timestamps. In this way, label 3 indicates frames without voice activity. Although our dataset is focused on SCD, these annotations will enable the model to perform OSD and VAD also.

3.2.2 Accent Classification Annotation

The labelling process for accent detection differs considerably from the process applied to SCD and PBD (see above). The SBCSAE includes the city and state from the United States corresponding to each one of the conversations as part of the metadata of the audio. For this reason, it has been necessary to label the whole audio with its accent rather than splitting the audio into frames. This poses another challenge, that is, to merge the audio classification task with two audio frame classification tasks. To solve this, we have assigned the corresponding accent label to every frame of the audio and then reduced the set of frame labels to only one for the whole audio.

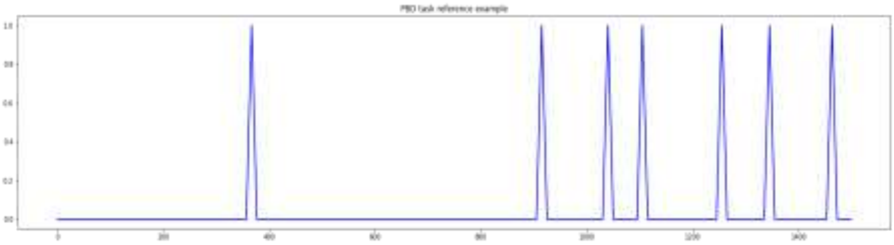
To establish the number of classes for this task, instead of assigning the labels based on the states, we have applied the classification of the major regional dialects of American English demarcated by Labov et al. [64]. This classification divides the map of the United States in six dialect regions. Table 1 shows the six dialects, the states that belong to each region and the labels that we have assigned for each dialect to prepare the data for this task.

Table 1. States included in the SBCSAE per dialect region, plus the label assigned to each region.

Regional dialects	**States**	**Label**
Inland North	Illinois, Wisconsin, Michigan	0
New England	Massachusetts, Vermont	1
Mid-Atlantic	Delaware, Pennsylvania,	2
South	Alabama, Texas, Kentucky, Louisiana	3
Midland	Indiana, Kansas	4
West	Montana, California, New Mexico, Arizona, Oregon, Washington, Nevada, Idaho, Colorado	5

3.2.3 Automatic Annotation Process

Once the labelling process is completed, the annotation files created from the SBCSAE are converted to the desired format (see sections 3.2.1. Audio frame labels and 3.2.2. Accent classification annotation). In order to automate the process, various Python scripts have been designed to streamline a variety of sequential tasks. The first task consists in splitting the audios into chunks of 30 seconds with a 15 second overlap between one audio and the next, to avoid context missing. Then, reference labels for PBD and SCD tasks are generated from the timestamps in the original annotations, and the speaker labels. The result is a set of 1500 labels for each task. Figure 1 shows example representations of the set of labels for PBD and SCD. The last script assigns the labels corresponding to the dialects according to the name of the state which appears in the metadata. The part of the scripts that perform the extraction of the key information were coded using regular expressions. The extracted data was saved as JSON files.



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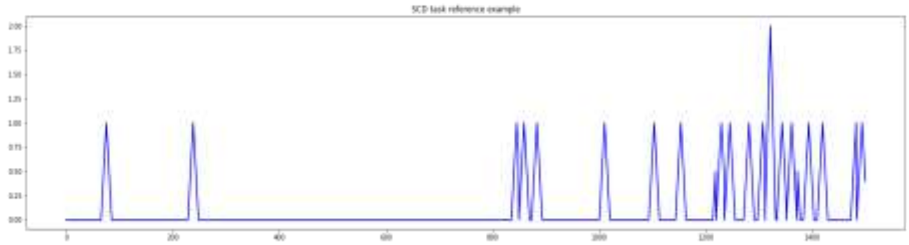

Figure 1. Examples of the reference label sets for PBD and SCD.

Once all the conversion and annotation processes described have been performed, the target dataset has been created through the *datasets* package from Huggingface[2]. This package allows the organisation of the dataset in three splits: train, test and validation. The entries inside each one of the splits contains the attributes "path" and "label". The "path" is the absolute path to the audio file and the "label" includes the three set of reference labels, one set for each task. After the generation of the dataset format, the entries are randomly divided into the three splits as follows: 80% of the dataset for training, 10% for testing and another 10% for validation.

3.3 Model Architecture and Experimental Design

Wav2Vec 2.0 (hereafter referred to as "wav2vec2") is a pretrained speech model whose architecture is mainly based on Transformers [2]. The model has a structure of three main parts: the feature encoder, the context network and the quantisation module. The encoder consists of several blocks of temporal convolutions that normalise the speech input and outline the number of time-steps of the speech which, in their turn, serve as input to the context network. The context network is a Transformer NN which learns contextualised representations from the output of the encoder. The quantisation module discretises the output of the feature encoder via product quantisation for self-supervised training. Figure 2 shows an illustration of the wav2vec2 framework. This model is able to learn representations from speech audio in the same way language models learn linguistic representations from text, achieving better results in ASR than previous state-of-the-art models [2].

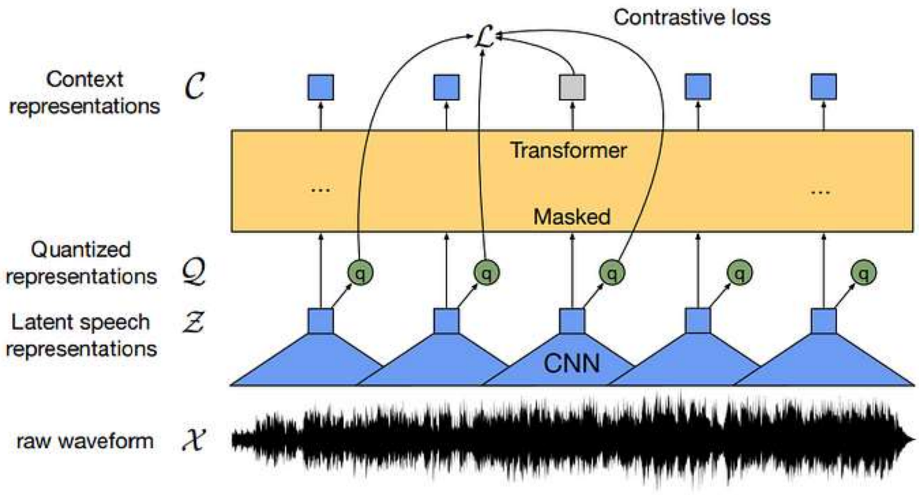

Figure 2: Illustration of the wav2vec2 framework by Baevski et al. *[2]*

In this study we have leveraged the language representations generated by wav2vec2 to perform a supervised learning experiment. This experiment has consisted in fine-tuning and validating a wav2vec2 model for multitask audio frame classification. To implement the desired architecture of

[2] https://huggingface.co/docs/datasets/index

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the model, we have used the *transformers*[3] package by Huggingface, which already includes an implementation of an audio frame classification architecture using a wav2vec2 encoder and a classification head on top. Given that we need three classification heads instead of only one, we have built our own architecture for audio frame classification based on the existing implementation in the transformers package. Each one of the classification layers performs its own task: one of them for PBD, another for SCD and the last one for accent classification. During training, the context representations generated by the wav2vec2 block are given to each one of the classification heads and they produce their own results. This process is illustrated in Figure 3.

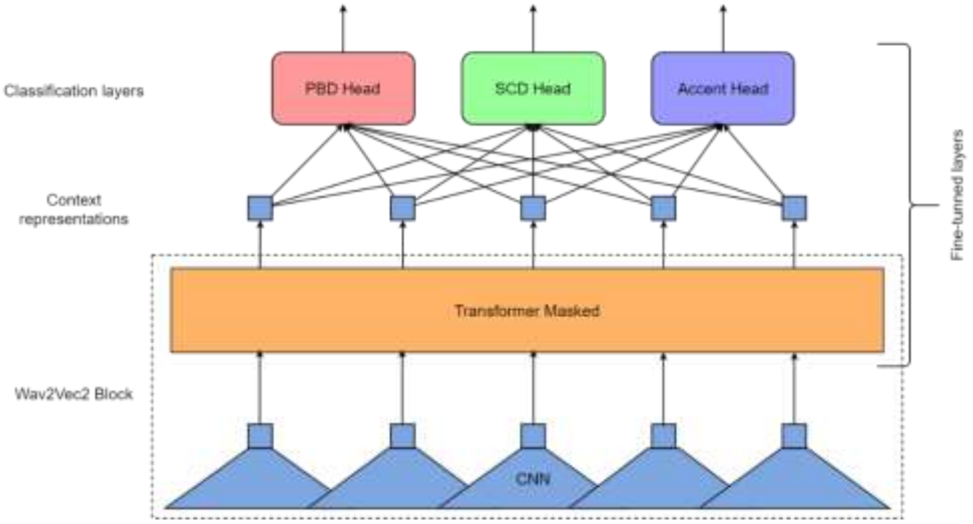

Figure 3. Model architecture and training process

3.4 Training, test and validation processes

Following previous studies (cf. section 2.5), we have focused on multitask training approaches as a key part of the training methodology. To train our model, we have used the wav2vec2 base model which can be obtained from the Huggingface models repository[4]. This is the wav2vec2 block of our architecture. As shown in Figure 3, only the Transformer layer of this block is fine-tuned during training. On the other hand, the three classification layers are randomly initiated and fully trained. The training is a supervised learning process, as the dataset includes the audio as inputs and the reference labels to adjust the loss function. For each step of the training, the context representations generated by the wav2vec2 block are given to the classification layers as the hidden states, and each one of the classification layers produces their corresponding label outputs. Following the starting hypothesis (cf. section 1. Introduction), the Transformer layer of the wav2vec2 block has been fine-tuned to extract the necessary features to perform the three classification tasks and generate the context embeddings that represent those features.

To achieve our goal, we have designed a composed loss function which is the combination of the loss from one of each classification layers. For PBD and SCD we have applied Mean-Squared Error (MSE) as the loss function, and Cross Entropy (CE) has been the loss function applied for Accent classification (AC). The reason for this difference in loss calculation is that for AC the labels are the same for every frame, therefore the output of the layer is converted into a probability distribution, instead of a set of labels. The composed loss is calculated as the weighted average of the three individual functions as follows:

$$\text{loss}=\text{loss}_{pbd}\,w_{pbd}+\text{loss}_{scd}\,w_{scd}+\text{loss}_{ad}\,w_{ad}. \quad (1)$$

[3] https://huggingface.co/docs/transformers/index

[4] https://huggingface.co/facebook/wav2vec2-base

The challenge of this loss function was to determine the optimal weights (w_{pbd}, w_{scd}, w_{ad}) applied to every task. To address this challenge, we have run a set of training experiments, using different parameters and weights. This process has helped to get the best context representations by fine-tuning the Transformer layer. The post-training results are presented below (cf. section 4. Results).

Next, the fine-tuned models have been evaluated through test and validation; for this task, the corresponding subsets from the dataset have been used. Testing has been done during fine-tuning, after each epoch. To this end, a composed metric has been used, similarly to what we did in the case of the loss function. However, we have used accuracy as a metric for accent classification instead of CE, and the MSE values from PBD and SCD have been inverted (1 - MSE). After training, the best checkpoint is selected based on the results of the test phases.

4. Results

Once the model has been fine-tuned, the validation is performed for each task separately by applying post-processing and different metrics. Post-processing consists in the reverse conversion of the label set of SCD and PBD classifiers by turning the labels into timestamps. After the reverse conversion, the F1 metric is applied to measure the performance of SCD and PBD tasks. In the case of the Accent classifier, its performance is measured using the accuracy metric (ACC).

4.1 Post-Processing Approach and Validation Measures

To convert the output labels given by the model back to timestamps, we applied different criteria to the PBD outputs and the SCD outputs. For the first task, the frames with label 1 are the PBs detected, although the model is not entirely accurate when assigning the labels. For that reason, we have established a threshold of 0.5. Every label bigger than this threshold is considered as a PB. In the case of SCD, the approach is similar, every frame with a label above 0.5 is considered a SC timestamp. We have also established thresholds for the labels corresponding to more than one person talking (1.5) and the labels for environmental sound or noises (2.5). For AC, no post-processing was needed.

After the post-processing was applied, we obtained two lists of detected timestamps for PBD and SCD respectively, and the corresponding references timestamps. To evaluate the performance of each task, we have applied several metrics, namely, Precision, Recall and F1. In the case of the AC output, we have measured the performance using ACC by comparing the reference set of accent labels and the output given by the Accent classifier.

4.2 Parameters Evaluation and Model Validation

The results discussed in the section are intended to fulfil a two-fold purpose. One is to validate the methodology and the trained models. The other is to find the optimal weights for the loss function. Tables 2-4 show the key results of each training, and their corresponding parameters, in terms of the applied loss weights and the number of epochs. For PBD and SCD task results, Table 2 (PBD) and Table 3 (SCD) contain the Precision, Recall and F1 values. In addition, Table 3 contains the Accuracy results for the Accent classification task.

Table 2. Validation results (%) for the PBD task

Models	Applied weights (w_{pbd}, w_{scd} and w_{ad})	Epochs	Precision	Recall	F1
1	0.38, 0.6, 0.02	10	63.49	50.43	56.21
2	0.33, 0.33, 0.33	20	67.19	44.24	53.35
3	0.4, 0.4, 0.2	20	66.66	60.67	57.58

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4	0.4, 0.5, 0.1	20	68.83	49.82	57.8
5	0.38, 0.6, 0.02	20	69.56	58.3	64.44
6	0.39, 0.6, 0.01	50	75.29	**75.9**	75.59
7	0.399, 0.6, 0.001	50	**78.73**	75.01	**76.78**
8	0.299, 0.7, 0.001	50	76.02	71.21	73.54

Table 3. Validation results (%) for the SCD task

Model ID	Applied weights (w_{pbd}, w_{scd} and w_{ad})	Epochs	Precision	Recall	F1
1	0.38, 0.6, 0.02	10	63.2	42.8	51.04
2	0.33, 0.33, 0.33	20	61.43	33.6	43.45
3	0.4, 0.4, 0.2	20	62.43	38.16	47.37
4	0.4, 0.5, 0.1	20	63.07	43.88	51.76
5	0.38, 0.6, 0.02	20	62.18	57.49	59.74
6	0.39, 0.6, 0.01	50	70.89	72.72	71.79
7	0.399, 0.6, 0.001	50	69.74	**75.39**	72.45
8	0.299, 0.7, 0.001	50	**74.78**	74.46	**74.12**

Table 4. Validation results (%) for the Accent classification task

Model ID	Applied weights (w_{pbd}, w_{scd} and w_{ad})	Epochs	Accuracy
1	0.38, 0.6, 0.02	10	99.46
2	0.33, 0.33, 0.33	20	99.46
3	0.4, 0.4, 0.2	20	99.28
4	0.4, 0.5, 0.1	20	99.28
5	0.38, 0.6, 0.02	20	**99.82**
6	0.39, 0.6, 0.01	50	**99.82**
7	0.399, 0.6, 0.001	50	83.27
8	0.299, 0.7, 0.001	50	92.63

In the three tables, each entry corresponds to the results from the model trained using the indicated weights for the loss function and the number of epochs. Besides, entries are ordered by the number of epochs, since we have observed that this parameter has the higher impact on the results. This can be noticed in the results from models 1 and 5. Model 5 has achieved a higher punctuation in all three tasks, even though both models have been trained with the same weights. No improvements can be observed in learning for more than 50 epochs, which justifies the maximum number of epochs (50) presented in the tables.

The results obtained during the fine-tuning of the applied weights indicate that the task that presents most problems for the models to predict is SCD. This is not unexpected, as the references from SCD task present higher variations at labels per frame than the other two (see 3.4). On the contrary, the high accuracy levels achieved at the Accent classification task show that this is the task that presents less difficulties. Since the model only needs to predict one label for the AC task, the high difference in the results between this task and the other two is not surprising. This explains why the weight for Accent classification showed the highest decrement, whereas the weight for SCD is increased in each training by the highest factor (see 3.4).

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Finally, our findings suggest that model 8 is the one that exhibits the best performance. Even if the results for Accent classification and PBD are affected negatively by the weights of this model, it shows an appropriate balance in performance for the three tasks.

5. Discussion

From the perspective of previous studies, this is not the first time that wav2vec2 is leveraged to perform PBD in a single task environment or leveraged to perform multitask speech processing. In [63], the authors present a methodology to fine-tune a wav2vec2 model to detect PB on Czech speech data, relying solely on acoustic information. An extended approach based on the previous one, was also applied for multitask speech processing on English data in [57], where the trained model performs SCD, OSD and VAD as different tasks. Regarding other NNs architectures, a few studies have introduced multitask or joint learning approaches for SCD, PBD and AC [33,43,58]. In [30] fine-tuned Whisper models for PBD on the SBCSAE are presented with satisfactory results, although their acoustic model performance was worse than their lexical model. Referring to Accent classification, the work in [65] presents a particular Multi Kernel Extreme Learning Machine (MKELM) architecture which has achieved similar scores than other DNNs architectures.

Given the possibilities of Transformer models for speech processing, the objective of this work was to fine-tune a wav2vec2 model with three classification layers to perform PBD, SCD and AC by relying only on acoustic information. We have tested our method on spoken English by using the SBCSAE corpus, like most of the models analysed in this study. To the best of our knowledge, this is the first experiment that applies one single model to perform the three target tasks at the same time. The results obtained during the fine-tuning experiments show that our model can achieve a performance score close to previous methods or even higher.

A comparison between our model and the most relevant previously proposed models is highlighted in Table 5. This comparison shows that our model has achieved slightly lower performance scores for SCD and PBD than previous methods, but its performance on AC is the best.

Table 5. Summary of results from previous studies and our results

Models	PBD Score (% F1)	SCD Score (% F1)	AC Score (% Accuracy)
[63]	82.73	-	-
[57]	-	90.79	-
[33]	91	-	-
[43]	-	88.32	-
[58]	-	-	75.2
[30]	73	-	-
[65]	-	-	84.72
Our model	**73.54**	**74.12**	**92.63**

Our model exhibits lower performance for PBD than the models presented in [33] and [63], but higher than the model presented in [30]. In [63] the described method is applied to the Czech language and the model presented in [33] is trained on text information, not only on acoustics/audio data. This explains the difference in performance compared to our model. On the other hand, [30] is the only approach that has used the same corpus (SBCSAE). The performance of this model, which relies solely on acoustic information, is slightly lower than our model's performance. Regarding the SCD task, our model has the lowest performance score on the table, although the three models were trained on English corpora following multitask approaches. However, the architecture and the tasks of our model are more complex than the previous models, which can explain the lower results. Finally, for AC, our model shows better performance than previous works. The main differences in

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this case are that the model in [65] is not a Transformer model and the approach applied in [58] combine ASR and AC.

In addition to the mentioned differences between our work and previous studies, it is important to note that, except the model described in [57], this is the only model that performs three speech processing tasks. In terms of model size, adding a new classification layer does not have an important impact, keeping the model size almost the same. This means that our model requires one-third of the memory compared to single-task models that perform the same three tasks, allowing for more efficient and cost-effective use of resources.

6. Conclusions and Future Work

Following our initial hypothesis, we assume that speech representations from the wav2vec2 framework could be leveraged in multitask speech processing. In this line, the main aim of this work was to demonstrate that a single wav2vec2 acoustic model can be fine-tuned, using joint learning techniques, for PBD, SCD and Accent classification. Our findings confirm our hypothesis: our model (trained and validated on the SBCSAE) is the best performing one, as it has achieved an F1 score of 0.74 for PBD and SCD, and a 0.93 Accuracy score for Accent classification.

To the best of our knowledge, ours is the first fine-tuned speech model which can perform all three PBD, SCD and Accent classification tasks by relying solely on acoustic information. This can be particularly useful in situations where no transcriptions or other language data are available. These tasks can be applied to speech pre-processing and segmentation, which can help to improve speech recognition performance in terms of precision and resource optimisation. This is the main contribution of this study. Another contribution is the data preparation process applied to the SBCSAE, which has been fully automated. This makes the process reproducible, scalable and transferable to other timestamp annotated corpora (with some minor adjustments, if needed). Finally, the proposed model architecture further advances the state-of-the-art fine-tuning methods, as the classifier layers can be trained to perform any audio frame classification task, which means that our model can be easily adapted to fine-tune models on other corpora.

The scope of this study was limited in terms of metrics and the relatively small data sample. It would be worth considering further complementary metrics, such as coverage, and measure training, as well as inference times of the models. But the most important limitation is related to the data used for training and validation. Our findings suggest that better results could be achieved by expanding the train and validation dataset with more speech corpora. Despite the significant contributions of our study, the issue of data size is an intriguing one which could be usefully explored in further research. To this end, we intend to repeat the experiments using more English datasets, in addition to the SBCSAE, to train and validate our model. In addition, several issues related to the limitations of our study remain to be solved. For instance, we will apply more metrics to expand the evaluation of the methods analysed. Finally, a natural progression for this work would be to test our model on other languages and on multilingual data (e.g., parallel corpora). In addition, our methodology could be applied to test other speech models and compare the results. Another possible study could be to leverage our model on cascaded or multi model speech systems, for instance, in a complete speech recognition system. This would be a fruitful area for further work.

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